Nerfs, Buffs and Bugs – Analysis of the Impact of Patching on League of Legends

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***Abstract*—While traditional software patches primarily fix bugs, modern online computer games use patches to change gameplay, as well. Despite the importance of gameplay changes for both game players and game designers, to the best of our knowledge, there are no published results nor available 3rd party Websites that analyze game data and patch data. We analyzed the effects of patches on gameplay in League of Legends (LoL), a popular online game created by Riot Games. Our methods: a) harvested all available patch data – over 160 patches with over 7700 changes – classifying patches based on a novel taxonomy; b) gathered game statistics from over 11,000 players in over 465,000 games; and c) analyzed both the patch data and game data, with emphasis on correlations. In addition, we developed a publicly accessible Web site that allows for interactive exploration of the game data and patch data. Analysis of the data shows that Riot patches LoL gameplay an average of twice each day, about ten times more often than Riot patches LoL bugs. Patches tend to keep all player-chosen champions close to a win rate of 50%. While most patch gameplay changes can be categorized and even quantified numerically, the impact of combined changes are not always straightforward and interpretation of patch text is required in order to understand the full impact.**

***Keywords*—Game Analytics, Co-op, Game Balance, Patch**

I. Introduction

Traditionally, computer games were released with all major content and game features in place and, hopefully, most bugs removed. If fixes or improvements were needed, well-known software engineering techniques called *patching* was used to apply new computer code/data to the game. However, while traditional patching was used primarily to fix bugs or improve performance, many modern games use patching to adjust game balance and add content to the game. In fact, many games are intentionally released without all game content in place and even without all gameplay elements fully vetted. Game patches are subsequently pushed out, changing the game with additional game content, adjusting the games rules and tilting the game balance – all of which effectively changes the gameplay for current players.

A popular example of just such a game is *League of Legends* (LoL, Riot Games, 2009). LoL is perhaps the most popular computer game in the world based on hours played per month [1], with 27 million players each day and 7.5 million simultaneous players at peak times [2]. As part of the eSports scene, LoL is lucrative business for some players, too, with a professional player circuit and tournaments with prize pools over $2 million [3], [4] USD, among the largest in competitive gaming history [5]. Competitive LoL matches require close collaboration amongst teams of players (typically five on each side), with players choosing and playing avatars (champions) in a specific role (e.g., healer, fighter) to help the team.

Since it's release in 2009, LoL has been patched over 160 times,[1] an average of about 1.5 patches per month. LoL uses both traditional software patches (that both fix and improve software) as well as modern game patches (that release new game content and adjust game balance). These patches have introduced significant amounts of new game content, roughly doubling the number of champion choices available to players since release, and altering the game balance for active players. Adding game content and changing game balance this way is critically important to game designers, since it keeps the game fresh for current players, and players since game balance has a major impact on game enjoyment [6]. Despite this importance, there has been little formal analysis of the effects of patching on gameplay, thus presenting an opportunity to better understand, and perhaps improve, modern game patching.

Riot Games provides access to extensive data on previously played LoL games through an online database.[2] There are numerous 3rd party Websites that use the Riot database to present game data that is helpful to both players and game designers. For example, two popular Web sites, LolKing[3] and OP.GG,[4] provide data on in-game choices players make and their impacts on winning/losing games. While many players may only wish to know about the latest (patched) game version, studying past patch changes can help players and game designers predict how current patch changes might affect the game.

Unfortunately, to the best of our knowledge, there are no 3rd party sites that have historical game data going back more than a few months, nor are there 3rd party sites that analyze patch content in any quantifiable way. Lacking from all 3rd party LoL sites, and published literature for all games, is analysis correlating game data with patch changes in order to better understand the implications that patches have on the game. As-is, 3rd party Websites require users to manually correlate game data with patch data, if patch data is even provided, and

[1] http://leagueoflegends.wikia.com/wiki/Patch
[2] https://developer.riotgames.com/
[3] http://www.lolking.net/
[4] http://www.op.gg/

make it impossible to do correlations for historic game data.

In order to analyze the effects of patching on League of Legends gameplay, we first developed a method to gather a large, random sample of game data from the Riot game database. Our gathering process yielded data on over 11,000 players in over 450,000 ranked games from Seasons 4–6. We also developed a method to harvest and classify LoL patch notes, devising a novel taxonomy of the types of changes relevant to both software fixes and improvements and gameplay changes. Using our method, we extracted and classified all available LoL patch notes from pre-release Alpha through Season 6, yielding over 7000 patch notes from 164 patches. In order to allow for interactive exploration of the patch data in relation to the game data, we developed a novel Web site[5] that enables users to select LoL avatars and investigate how patch changes have impacted their performances over time.

Our analysis of game data shows the win rates for champions chosen by players to be mostly normally distributed around 50%, but with fewer than expected champions much higher or much lower than this rate, probably due to patching. Champion picks are not at all equal, with a heavy skew for the most popular champions. Ban rates are even more skewed, with a small percentage of champions being banned the most.

Our analysis of patch data shows a fairly steady rate of changes which would not be expected for a mature, stable game. The majority of changes are not fixes or visual improvements, however, but are changes to the gameplay itself in the form of adjusting balance and adding new content.

Correlating game data with patch data shows changes are indeed designed to adjust win rates for champions with a lower than average win rate while reducing win rates for those with a higher than average win rate. However, more detailed analysis also shows that simply counting patch changes does not always accurately predict the effects on win rates.

Our work makes several key contributions: 1) aggregate analysis of the most important in-game statistics for LoL players, accompanied by a Web site that enables interactive exploration. While other 3rd party Web sites have similar information, we are the first to provide such information in a historic context; 2) comprehensive classification of all LoL patch notes, categorized into a taxonomy that allows for exploring the relationship between the kind of patch and the effects on gameplay; and 3) analysis of the correlations between patch data and gameplay.

The rest of this paper is organized as follows: Section II describes background and related work; Section III details our methodology for gathering patch and game data for LoL; Section IV presents the LoL Crawler Website for interactive exploration of LoL patches and game data; Section V analyzes the gathered data; and Section VI summarizes our conclusions and provides for some possible future work.

[5]http://lolcrawler.cs.wpi.edu/

II. Background and Related Work

This section provides background information on LoL (Section II-A) and patching (Section II-B), particularly as is relates to LoL, and summarizes the lack of related work on analyzing game patches (Section II-C).

A. League of Legends

League of Legends (LoL) is a multi-player online battle arena (MOBA) game where players are matched into two opposing teams. While there are several game variants for casual players, most competitive (also called *ranked*) matches and all professional matches are played on a standard game map with 5 players on each side. The objective is to destroy the opposing team's headquarters. Once matched to a team, each player chooses one out of 128[6] different characters, called champions, to control during the game. Gameplay consists of controlling the champion to fight opponent champions as well as other lesser monsters on the game map, ideally working cooperatively with teammates. Champions vary in their in-game abilities (e.g., method of attack, types of spells) and attributes (e.g., amount of damage, rate of attack) and are enhanced by skills and items gained during the game.

In ranked matches, before the game starts, players alternate picking champions and there can only be one of each champion type - i.e., there are 10 unique champions each game. Before champion selection, each team bans 3 different champions, prohibiting either team from choosing them for the game - i.e., there are 6 unique champions banned each game.

The best LoL teams are those whose players cooperate well, with players using their champions for different positions on the team (e.g., a tank to absorb damage or a healer to aid wounded allies). In fact, Riot designs champions with specific team roles in mind. The most basic roles include damage dealers, tanks (those who can take a lot of damage), and utility (healing friendly champions or controlling enemy champions). Some champions can fulfill multiple roles depending on how they are played and the in-game items purchased.

League of Legends only allows players to compete against other players in the same geographic region. Regions include Brazil, Europe East and West, Japan, Latin America North and South, North America, Oceania, Russia, and Turkey. Competitive players are ranked into tiers of Bronze, Silver, Gold, Platinum and Diamond with 5 divisions in each tier. The vast majority of ranked players are in the Bronze through Platinum tiers. The top two tiers, Master and Challenger, have one division each, and Challenger has the best 200 players in a geographic region.

B. Patching

In computer games, "patching" is the process of changing an existing game. While there are thousands of changes made to a

[6]As of February 2016, the time of this study.

game before it is released, after release the changes are added on top of the existing game from the player's perspective, hence the name *patch*.

Many modern day games develop internally until a playable version of the game can be played externally, but that game version does necessarily have all planned game content. The intent of the developers is to release the game externally, then patch the game with both fixes to problems as they are revealed, as well as add additional content as the player base grows.

For League of Legends, patches contain new game content, balance changes, bug fixes, or technology improvements [7]. While bug fixes and technology improvements are likely welcomed by nearly all players, new game content and balance changes are different. Effectively, new game content in the form of (for LoL) new champions, new items, new abilities and even new game maps, requires a player to re-learn aspects of the game that s/he may have already mastered. Balance changes are typically somewhat easier since the gameplay remains the same, just the relative effectiveness of different actions changes, but still require the player to adjust his/her play.

C. Related Work

While there is considerable research on the use of patches to address software security, e.g., [8], such patches do not typically enhance the software with new features.

There has also been research on traditional software patches, e.g., [9], but not as the patches relate to games and not with any analysis of the effects of the patches on players/users.

There is some published research on data analytics, e.g., [10], an important area for game development, but none of it has focused on analyzing patches for games nor downloadable game content.

III. Methodology

Our methodology to analyze the effects of patching on LoL gameplay is as follows:

1) Gather data on LoL games (see Section III-A).
2) Harvest data on LoL patches (see Section III-B).
3) Build a Web site to allow for interactive exploratory analysis (see Section IV).
4) Analyze the data (see Section V).

A. Gathering Game Data

Riot Games provides access to their game database through their Application Programming Interface (API),[7] a method to access structured game data in a secure and reliable way. Once a developer key is obtained (free with any LoL user account), access is gained through HTTP GET requests with the output returned as plain text in JavaScript Object Notation (JSON) format.

The API provides complete data on previously played ranked games for all players from Season 4 onward,[8] and includes information on champions picked and banned as well as the champions that won.[9]

Since the default key used for API access only allows for a maximum of 10 requests every 10 seconds and 500 requests every 10 minutes, Riot approved our request for a production key that enables 3000 requests every 10 seconds and 180,000 requests every 10 minutes.

The API provides no built-in functionality for extracting a random game nor even a game with specific attributes in mind (e.g., player ranking). Nor is retrieving the full population of games feasible given that there are over 1.5 million players on the North American server alone, many with hundreds and even thousands of matches in their histories. Instead, a novel method to gather a representative sample from the population of all ranked games is needed.

Our approach to sampling proceeds with "seed" players – 25 players, one from each division from each tier[10] – randomly selected from players listed at LolKing,[11] a 3rd party Web site that lists all players by tier and division. The LoL API provides the history of ranked matches for each seed player which is used to collect additional id's of players that competed with the seed player in a ranked game, hence likely have similar rankings. The process is repeated until there are enough unique players selected. From these players, game histories are combined, duplicate ids removed, and a random sampling of games chosen from this combined pool.

Once the list of games is compiled, the full match details can be pulled from the Riot API. In our case, we extracted champion data – winners, losers (both of which were "picked") and those banned.

B. Gathering Patch Data

Unlike LoL game data obtained through the Riot API, patch notes are not provided in any structured form. Instead, patch notes are released as human-readable text. Fortunately, formatting and language is fairly consistent across patches in relation to the type of change, allowing some automation to categorize the patches.

After manually examining the patches, we created a taxonomy for classifying the individual patch notes, depicted in Figure 1. Each patch note is one change to the game and is classified into one of the leaves in the taxonomy.

[7] https://developer.riotgames.com/

[8] Prior to Season 4, game data is incomplete and win rates for champions cannot be computed.

[9] Additional game data is available, e.g., gold earned, but gathering and analysis is left as future work.

[10] Excluding Master and Challenger, since the vast majority of players are in Bronze – Platinum.

[11] http://www.lolking.net/

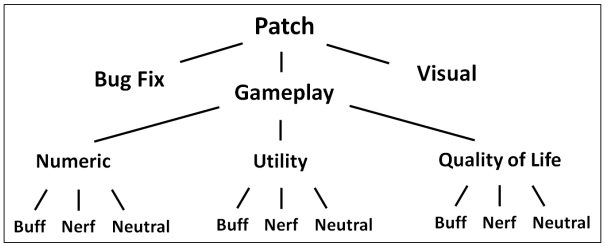

Figure 1. Patch Taxonomy. Leaves are the final classification for each patch note.

Broadly, there are three main types of patch notes/changes:

- *Bug fixes* – bug fixes correct inadvertent mistakes in the game (e.g., bug fixed where interrupting player action would render champion unable to cast spells).
- *Visual* – visual changes modify the look of the game of either the map and/or a champion, including graphics, skins or other animations (e.g., new visual particles added to a spell).
- *Gameplay* – gameplay changes affect the champions and their interactions.

For issues related to game balance, gameplay changes are of the most interest. Gameplay changes can be further categorized as:

- *Numeric* – Numeric changes are quantified modifications to game statistics for champions (e.g., amount of damage dealt per attack).
- *Utility* – Utility changes affect how a champion's ability interacts with other aspects of the game (e.g., an added effect to slow an opponent hit by a spell).
- *Quality of Life* – Quality of life changes affect the ease of use of a champion (e.g., an added visual indicator to better determine where a spell will hit).

Each gameplay change can be further identified based on the effect the change has in terms of the champion's relative strength:

- *Buff* – A buff increases the strength of a champion (e.g., base armor increased from 19 to 23).
- *Nerf* – A nerf decreases the strength of a champion (e.g., spell radius reduced from 350 to 300).
- *Neutral* – A neutral change is neither clearly a nerf nor a buff (e.g., base damage changed from 100 at level 1 and 500 at level 3 to 150 at level 1 and 450 at level 3 – the ability is being buffed at level 1 (going from 100 to 150 damage), but also nerfed at level 3 (going from 500 to 450 damage)).

From visual inspection, gameplay changes are the most frequent, followed by visual updates and then bug fixes. For gameplay changes, numeric changes are the most frequent, followed by utility changes and quality of life changes. Numeric changes to gameplay can often be detected from words such as "increased," "reduced" and "modified" followed by a number – whether such a term is a nerf or buff depends upon the context. Quality of life changes do not have consistent language to help with categorization. Utility changes occur most often when a champion is reworked (i.e., the abilities of the champion are significantly changed), but still lack keywords that can aid in categorization. The terms "fix(ed)" and "bug" signify a bug fix and the terms "visual," "animation," and "update(d)" generally signify a visual update.

In our classification, false negatives occur when a change is not detected and no categorization is made. False positives occur when a change is detected but is incorrectly categorized. True positives occur when a change is detected and correctly categorized.

We obtained all available patch notes from the League of Legends Wiki,[12] a community-edited resource with information on each champion based on patches released by Riot. For each champion, we extracted the patch note text, categorized it and stored it in a local database for analysis.

Categorization then used pre-determined keywords for automatic classification for bug fixes, visual changes and numeric gameplay changes. Automatic classification of quality of life and utility gameplay changes was not done as this greatly increased false positives, while the resulting false negatives were easier to catch manually. The final manual categorization step classified any remaining unclassified changes and corrected any mistakes made.

IV. LoL Crawler Web Site

In order to allow for interactive exploration of the game data – specifically, the champion win, pick and ban rates – and the patch notes, we implemented a Web site that provides for manual analysis of our gathered data. Our publicly accessible Web site:

http://lolcrawler.cs.wpi.edu/

is called *LoL Crawler*. It allows users to select a champion and then simultaneously graphs game rates versus patch for that champion and links the graph to champion patch notes. Lol Crawler is implemented in PHP, nodeJS[13] and C#.

The LoL Crawler home page provides a brief overview text of the site at the top of the page and in the middle presents a scrollable list of champions, shown with their images and names. This champion list is a selection interface similar to that used by players in the LoL client to choose a champion before a game starts, so should be familiar to many users.

Selecting one of the champion images/names takes the user the data page for that champion, depicted in Figure 2. The top of the page shows a graph of the champion rates. The x-axis is the patch and the y-axis is the rate (percent). Win rate, pick rate and ban rate are selectable on the right, toggling them on and off (in Figure 2, they are all on). The x-axis is scaled to

[12]http://leagueoflegends.com/wikia.com/
[13]https://nodejs.org/en/

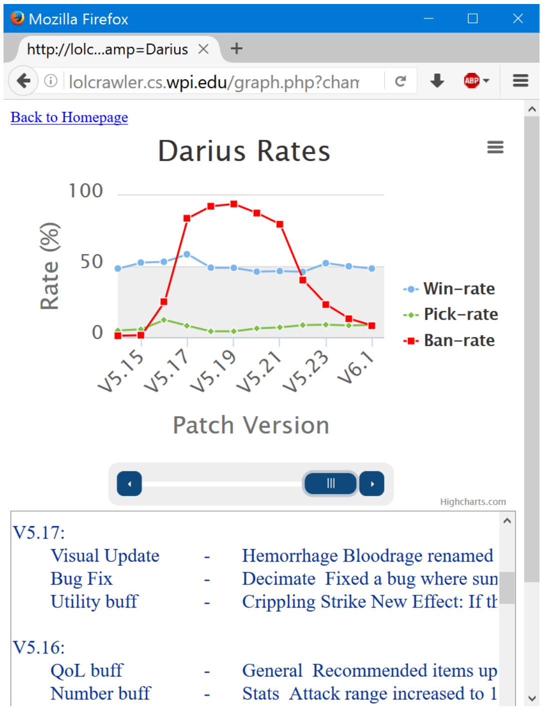

Figure 2. Champion data page from the LoL Crawler Web site.

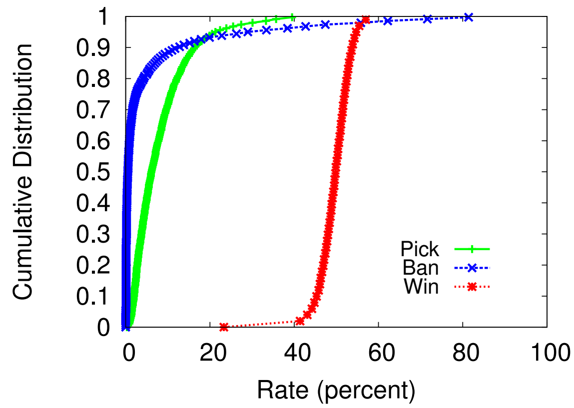

Figure 3. Win, pick and ban rates for all champions calculated for each patch.

show a reduced number of patches to aid readability but is scrollable (left and right) over the full set of patches.

The bottom half of the page shows the patch notes, indicating the patch version number and the champion-specific patch notes each contains. Our patch note categorization (see Section III-B) is also shown along with the accompanying text. Hovering over a data point provides more information about the resulting rates from that patch by showing a tooltip above that point. Clicking on a data point scrolls the patch text to the location of the corresponding changes.

V. Analysis

This section first analyzes the game data gathered through the Riot API (Section V-A) and the patch data gathered through our classification process (Section V-B), then explores relationships between the two (Section V-B).

A. Game Data

We applied our sampling process (see Section III-A) using the LoL North American geographic region, resulting in 465,000 ranked games from Season 4 to the start of Season 6 (v6.1) randomly selected from the combined history of about 11,000 players. Each game provided the 10 unique champions picked, which champions won and which lost, as well as the 6 unique champions that were banned. In total, the process yielded statistics on nearly 7.5 million champions in games.

From the data gathered, we computed the most fundamental statistics on the selection and then effectiveness of player choices – specifically, the win rate, pick rate and ban rate for each champion, computed separately for each patch (e.g., win rate for the champion Darius for patch number 157 is computed from the number of patch 157 games Darius won and the total number of patch 157 games Darius played).

Figure 3 depicts a graph with the cumulative distribution functions for each rate, computed as a percentage calculated for each champion for each patch. The x-axis is the percentage and the y-axis is the cumulative distribution. From the graph, the win rates are centered around 50%, which makes sense since in a given game, half the champions win and half lose. Note, the individual champion win rates are not all the same – if they were, they would all have the same rate shown as a vertical line at 50%. Instead, the bulk of the distribution is between 45-55%, with the "S" shape suggesting the values are normally distributed.

To test for normality, Figure 4 depicts a quantile-quantile (Q-Q) plot comparing the win rate distribution to a normal distribution. The x-axis is the normal distribution quantile (z-score) and the y-axis is the win rate. The sorted win rate values are plotted as points, with the diagonal line being $y = x$. In a Q-Q plot, if the distributions are similar, the points will lie upon the line.

In the case of Figure 4, the data does look normal and the probability plot correlation coefficient is 0.991. However, the tails of the distribution do not fit a normal distribution as well as the rest of the distribution, where there are fewer win rates than would appear normally. Riot has most likely intentionally addresses outliers by keeping champions from having significantly higher win rates (too strong) or significantly lower win rates (too weak) than a 50% average.

The pick rate distribution in Figure 3 is more skewed than the win rate distribution. The pick rates range from about 5% for half of the distribution to over 20% for top 2% of the distribution. The top 5 pick rates are for the champion Lucien for patches 126 (v4.8), 127 (v4.9), 134 (v4.16), 135 (v4.17),

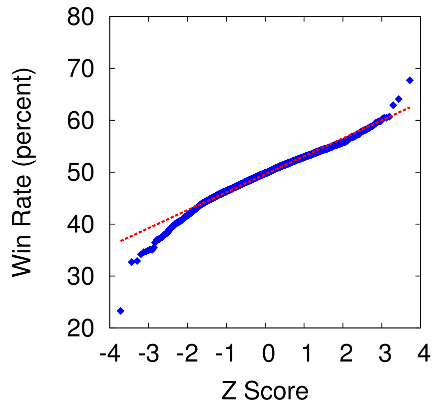

Figure 4. Graphical normality test (Q-Q plot) for win rate distribution.

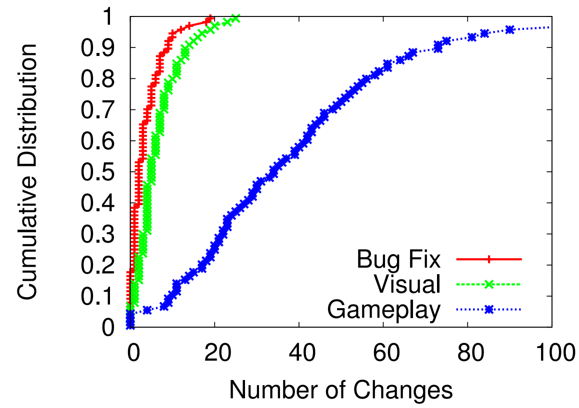

Figure 5. Cumulative distribution of taxonomy level 1 changes.

TABLE I
SUMMARY STATISTICS FOR RATES.

Statistic	Win Rate	Pick Rate	Ban Rate
Min	23.3 %	0.3 %	0.0 %
Median	49.8 %	6.1 %	0.5 %
Mean	49.6 %	8.1 %	4.9 %
Std Dev	3.4	6.8	12.4
Max	67.7 %	50.2 %	94 %

TABLE II
SUMMARY STATISTICS OF RATES FOR CHAMPION ROLES.

Role	Win Rate	Pick Rate	Ban Rate
Assassin	49.0 %	4.3 %	6.9 %
Fighter	50.9 %	9.0 %	5.8 %
Mage	49.7 %	7.5 %	3.8 %
Marksman	49.8 %	11.4 %	1.8 %
Support	50.3 %	10.0 %	6.1 %
Tank	50.3 %	4.6 %	3.8 %

and 164 (v6.1).

The ban rate distribution in Figure 3 has the most skew, where 70% of the champions have a ban rate under 1%, but the top 2% of champions have a ban rate over 40%. The top 5 ban rates are for the champions Jax for patch 128 (v4.10), Sejuani for patches 147 (v5.8) and 148 (v5.9) and Darius for patches 157 (v5.18) and 158 (v5.19).

Table I provides the summary statistics for the rates.

LoL is a cooperative game where champions are designed to be played with a set team role during combat.[14] Table II provides the summary statistics for the rates from Figure 3 broken down into the designated champion roles. Win rates are near 50% for all champions, with Fighters slightly higher and Assassins slightly lower. Perhaps correspondingly, Assassins have the lowest pick rate. The Marksman has the highest pick rate and the lowest ban rate.

[14] https://support.riotgames.com/hc/en-us/articles/201752864-Choosing-the-Right-Champion

B. Patch Data

In total, as of the time of our analysis in February 2016, LoL had 164 patches with 7710 patch notes/changes. The automatic part of our system classified 67% of all changes with a true positive rate of 63.2%, a false negative rate of 33.0%, and a false positive rate of 3.8%. The precision and recall were 94.3% and 65.7%, respectively. Manual inspection fixed the miss-classified patches and classified the remaining 33% of the patch notes. No new false negatives or false positives were revealed and all true positives were confirmed.

LoL was in Alpha and Beta testing from February 2009 until its official release in July 2010. Since then, there has been approximately one competitive season each calendar year (i.e., Season 5 ended November 2015).

Major changes in LoL gameplay is from additional content in the form of new champions. While no patches after the Alpha and Beta seasons have added more than one champion at a time, the number of champions released has varied widely with season (year). Early seasons released more champions, as often as one champion every two weeks, while more recent seasons released fewer than one champion a month on average. As of February 2016, there were 128 champions total.

Figure 5 depicts a cumulative distribution function (CDF) of the top level – Bug Fix, Gameplay, Visual – changes to LoL based on our taxonomy (see Figure 1). The x-axis is the number of changes in a patch and the y-axis is the cumulative distribution. There are three trendlines, one for each type of patch change. Bug fixes, the most common patch in traditional software, are in the obvious minority for LoL with a median of only 2 bug fixes per patch. Visual changes to the game are only somewhat more common, with a median of 5 changes per patch. Contrast that with gameplay changes where the distribution is significantly shifted to the right, with a median of 34 changes per patch.

Figure 6 depicts a CDF of the second level gameplay – Numeric, Utility, Quality of Life – changes to LoL from

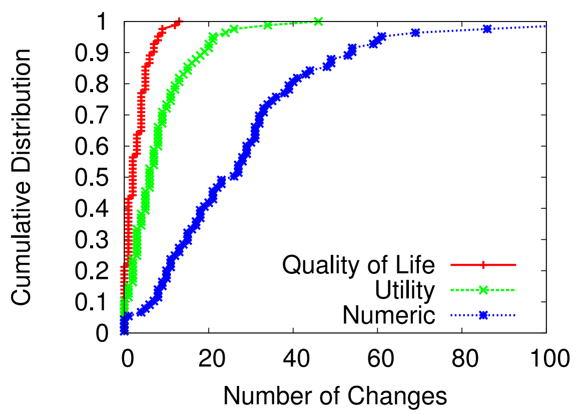

Figure 6. Cumulative distribution of taxonomy level 2 changes.

TABLE III
SUMMARY STATISTICS OF PATCH DATA.

Change	Min	Median	Mean	Std Dev	Max
Gameplay	0	34	39	29	223
Visual	0	5	7	6	34
Bug fix	0	2	4	4	24
Numeric	0	26	28	23	184
Utility	0	6	8	8	46
Quality of Life	0	2	3	3	13
Buff	0	16	19	19	159
Nerf	0	18	19	12	57
Neutral	0	3	4	5	24

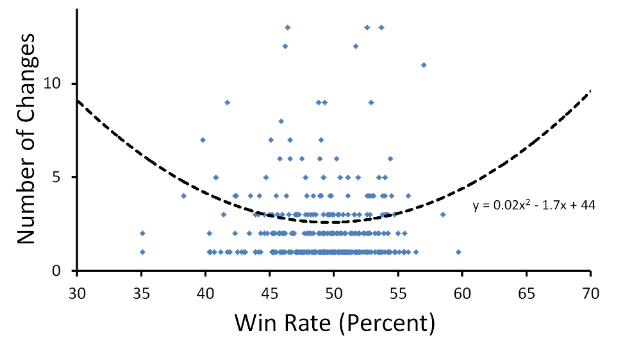

Figure 7. Number of changes versus win rate. Number of changes is count of patch notes applied to champion, win rate is computed after patch is applied.

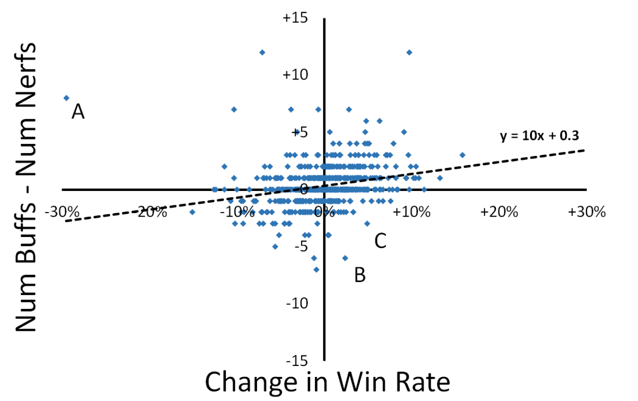

Figure 8. Buffs minus nerfs versus win rate. Count of buffs and nerfs extracted from patch notes, win rate is computed after patch is applied.

our taxonomy (see Figure 1). The x-axis is the number of changes in a patch and the y-axis is the cumulative distribution. There are three trendlines, one for each type of gameplay patch change. Quality of life changes are the rarest, perhaps because these are the most significant since they modify how a champion is played, and have a median of 2 changes per patch. Utility changes are more common with a median of 6 changes per patch. Numeric changes are the most common, perhaps because they are the easiest to code, and have a median of 26 changes per patch.

Analysis of third level – Buff, Nerf, Neutral – changes to LoL from our taxonomy (see Figure 1) shows nerfs and buffs are equally plentiful, with far fewer neutral changes.

Table III provides the patch data summary statistics.

C. Combined

As mentioned in Section V-A, the win rate distribution may intentionally have a restricted spread because Riot attempts to keep overall champion win rates as close to 50% as possible. Any win rate higher than 50% implies that the champion is giving the player an advantage (a dominant strategy) while any win rate lower than 50% implies the champion is giving the player a disadvantage (a dominated strategy). In order to maintain balance, Riot may choose to appropriately nerf and buff champions to keep win rates near 50%. Figure 7 depicts a scatter plot of the win rate against the number of changes for that champion. A best-fit quadratic regression for the data shows that as the win rate moves farther from 50% the number of changes in that patch for that champion increases.

There are several outliers in Figure 8 that are of interest with more in-depth analysis. Using our interactive LoL Crawler Website (see Section IV), the specific nerfs and buffs in the patch notes can be examined in conjunction with the subsequent win rate.

The point marked A in Figure 8 represents the champion Urgot for patch 134 (v4.15), where he had a decrease in win rate of 29.5% even though the patch contained 8 buffs. Before this patch, Urgot was an unpopular champion, with low win rates and pick rates. His pick rate doubled from 0.5% to 1% after this patch due to a minor rework containing several buffs and a bug fix. The influx of players that chose him after the patch likely had not previously played Urgot regularly, who is an somewhat odd and difficult to play champion, most likely causing his win rate to drop, despite the buffs.

Points B represents the champion Gangplank for patch 154 (v5.14), where he received a large rework of his abilities. Many of the changes were small nerfs to attributes such as armor and health that likely did not have a large effect on win rate. Many large neutral changes to his abilities altered how they fundamentally worked. From the patch wording, it was unknown whether these changes would be a net positive or negative, hence they were classified as neutral. However, the new abilities turned out to be effective and synergistic with one another, leading to an increase in win rate.

Point C represents the champion Kalista for patch 157 (v5.17) where she received three nerfs. Her win rate increased by 4.9% with no real explanation, as the nerfs were unambiguously negative. The most likely explanation is that changes to other champions caused the increase in win rate. For example, buffs were made to several Fighter champions that excel at killing Marksmen, such as Kalista, but Kalista is better than most other Marksmen at escaping, perhaps explaining why her win rate went up relatively to others, despite the nerfs.

VI. CONCLUSION

While traditional software patches typically only fixed bugs or tweaked performance, modern computer games often use software packages to adjust gameplay and even release more game content. League of Legends (LoL, Riot Games, 2009), one of the most popular online computer games in the world, uses software patches to add new player avatars (champions) and change the game balance for avatar combat.

Despite the importance of game balance to player satisfaction [6], there has been little analysis of the effects of LoL patches on gameplay. Existing 3rd party Web sites allow players to examine champion statistics for the most recent LoL patch, but do not provide for inspection of patch effects over time. Prior research has analyzed the impact of software patches, but primarily for traditional software and in relation to software security. To the best of our knowledge, there are no publications nor 3rd party Web sites that analyze LoL patches in conjunction with their impact on champion performance.

To analyze the impact of patching on League of Legends, our project gathered and analyzed over two years of LoL game data and over eight years of LoL patch data. Gathering game data required development of a methodology to obtain a random sample of LoL games from Riot and gathering patch data used a novel automatic classification technique to categorize patch notes from text Web pages. The game data was deconstructed into the most fundamental game attributes for LoL players – champion win rates, champion pick rates and champion ban rates. The patch data was categorized using a novel taxonomy that identifies patches based on their kind of change to a LoL champion and the relative change. In addition, we designed and developed a publicly available Web site[15] that allows for interactive exploration of game data and patch data for individual champions.

Analyzing game data for 128 unique champions played by more than 11,000 players in over 465,000 ranked games shows champion win rates are tightly clustered around 50%, normally distributed but with fewer win rates much higher or lower than 50% than expected. Pick rates and ban rates are significantly skewed, reflecting the disparate popularity of champions and perceived strength of opposing champions, respectively.

Analyzing patch data for more than 160 patches with over 7700 patch notes shows gameplay changes dominate, being 5-10x more numerous than bug fixes or visual changes to the game. On average, LoL has about 75 gameplay changes each month and only 4 bug fixes each month. Most (70%) of the gameplay changes are numeric increases (buffs) or decreases (nerfs) to champion abilities, but there are utility changes that make a champion easier to use and even quality of life changes that completely rework a champion. LoL has added over 40 completely new champions since the first season.

Analysis of game and patch data shows champions with win rates further from 50% are patched most, with buffs used to increase a champion's win rate or nerfs used to decrease it. Interactive examination of game data and patch data illustrates the impact of neutral changes, visual updates and bug fixes as well as champion reworks. Use of the Web site, as well as the analysis in the paper, should be useful for LoL players and game designers that want to better understand how current and future patches affect champions and gameplay.

Future work could include study of other LoL game modes (e.g., Dominion) and additional analysis of other objective game data available from Riot, such as individual champion statistics (e.g., kills/deaths/assists) and in-game currency and items. Other future work could analyze patch data in relation to game data for other games – those in the same genre as LoL are *Defense of the Ancients* (Valve, 2013) or *Heroes of the Storm* (Blizzard, 2015), but other game genres (e.g., first person shooter games) may use game patches differently.

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